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Power forecasting for a photovoltaic system based on the multi-agent adaptive fuzzy neuronet

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Abstract. This article presents a multi-agent adaptive fuzzy neuronet for a two days ahead forecasting of the hourly power from a photovoltaic system under random perturbations. In this research we consider a 5 KW Solar Power Plant for a residential building (model SA-5000M). The main objective of this research is to fulfil the multi-agent adaptive fuzzy neurone for hourly power forecasting for a photovoltaic system. The agents of the multi-agent adaptive fuzzy neuronet are fulfilled as two-layered recurrent networks. The standard Levenberg-Marquardt algorithm is described. The analysis of the evolving errors shows the potential of the multi-agent adaptive fuzzy neuronet in the hourly power forecasting for a photovoltaic system.

1. Introduction

Researches of a photovoltaic (PV) system which integrated in electric power systems gained a great attention in modern energetics. The power forecasting for a PV system is critically important for planning effective transactions in the electricity market, in order to provide reliable grid operation. The day-ahead market imposes penalties for a deviation from the approved and expected day-ahead schedules of the hourly power from a PV system. The deviation's tolerance is 5% of the total capacity of the PV system. The power fluctuations from a real-life PV system under random perturbations of cloudiness have complex dynamics. A clear sky index and a clearness index are typically used in the relevant technical literature to describe cloudiness. The important advantage of the clear sky index is the removal of daily and seasonal oscillations from insolation data to reveal fluctuation power content.

The neuronetbased solutions have been developed to approximate complex dynamics of the power from a PV system and show good performance. But there is a growing demand for an effective power forecasting model for a PV system. The effective approaches are those that provide solution based on intelligent algorithms. This paper presents a multi-agent adaptive fuzzy neuronet (MAFN) for a two days ahead forecasting of the hourly power from a PV system. Compared to existing fuzzy neuronets, including ANFIS, the MAFN is a Multi-Agent System. The algorithm of the agent’s interaction uses a fuzzy-possibilistic method. The agents of the MAFN are fulfilled based on recurrent networks. The training algorithm of the MAFN must find the optimal network configuration within an architecture space.

An automatic generation of the optimal architecture's parameters of a neuronet is the most complex task. Within a multidimensional search space, the training algorithm must find both positional and dimensional optimum. The effective network architecture is up-to-date designed by a human expert, requiring a thorough system's analysis and the trial-error process. This process is challenging because it requires fulfillment of the all conditions of optimal neuronet architecture. The global optimum provided by the multi-dimensional Particle Swarm Optimization (PSO) [1] process corresponds to an optimum MAFN architecture where the MAFN architecture's parameters (delays, a number of nodes in hidden layer, corresponded weights and biases) are generated from the global optimum. Furthermore, the multi-dimensional PSO provides a ranked list of MAFN configurations, from the best to the worst. This is an important information, arguing which configurations can effective solve a particular problem. The MAFN was fulfilled based on an extensive empirical database.

A database of the total power from a PV system, ambient temperature, meteorological parameters and insolation data was collected in the south-eastern part of Siberia, RF at the site of Abakan. In order to train the effective MAFN we use the algorithm, in which the multi-dimensional PSO [1] is combined with the Levenberg-Marquardt algorithm [2]. The multi-dimensional PSO is first applied to globally optimize the network's structure, and then the Levenberg-Marquardt algorithm is used to speed up the convergence process. The results of the MAFN on the challenging real-world problems [3-4] revealed its experimental validations and following advantages: it supports the real time mode and competitive performance, as compared to classical methods; a trained MAFN effectively processes noisy data. The simulation results show that proposed training algorithm outperforms multi-dimensional PSO and Levenberg-Marquardt algorithm in training the effective MAFN for the power forecasting for a PV system.

2. The power from a PV system

In this research we consider a 5 KW Solar Power Plant for a residential building (model SA-5000M). This PV system locates at the site of Abakan. Figure 1 shows a scheme of the PV system. This PV system includes six solar PV modules (model number: CHN250-60P), a solar regulator, a battery bank and an inverter.

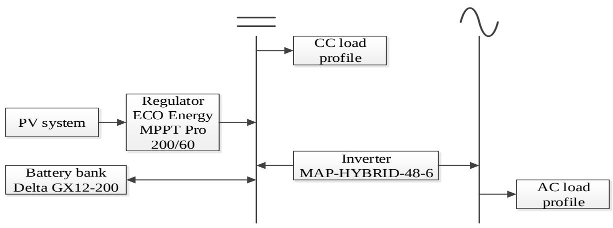

Figure 1. The scheme of the PV system.

The total rate of radiation G_C striking a PV system on a clear day calculated as follows:

$$Gc = Ae^{-km}(\cos\beta\cos(\phi_s - \phi_C)\sin\Sigma + \sin\beta\cos\Sigma + C/2 + (\cos\Sigma)/2 + p(\sin\beta + C)(1-\cos\Sigma)/2) \tag{1}$$

where m is the air mass, β is the altitude angle, φ_S is the solar azimuth angle, φ_C is the PV module azimuth angle, p is the reflection factor, Σ is the PV module tilt angle, C is the sky diffuse factor, A and k are parameters related to the Julian day number.

The surface irradiance is less than its corresponding extraterrestrial irradiance. The degree of attenuation depends from cloudiness. The surface irradiance fluctuates randomly. These fluctuations are closely related to the cloudiness' dynamics (figure 2).

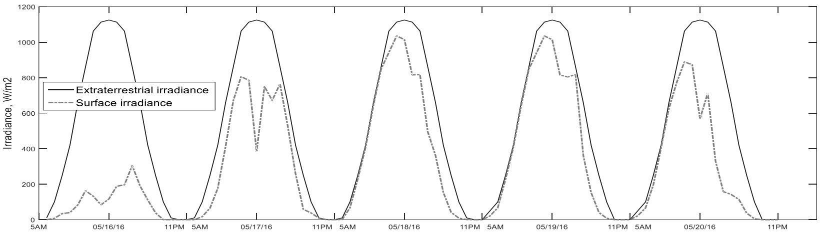

Figure 2. The extraterrestrial irradiance and the surface irradiance at the site of Abakan.

In order to evaluate influences of the deterministic solar geometry and the nondeterministic atmospheric extinction separately the clear-sky index is used. In this paper, the clear-sky index is defined as follows:

$$C = Gs / Gc, \tag{2}$$

where Gs is the surface insolation, Gc is the clear-sky model's insolation. The insolation is the integral of solar irradiance over a time period. The clear-sky model's solar irradiance calculates as (1). Figure 3 shows that the clear-sky index C is big and has similar shape under sunny days (05/18/16, 05/19/16) at the site of Abakan. In contrast, C is smaller and has more fluctuations on cloudy days (05/16/16, 05/17/16) than sunny days.

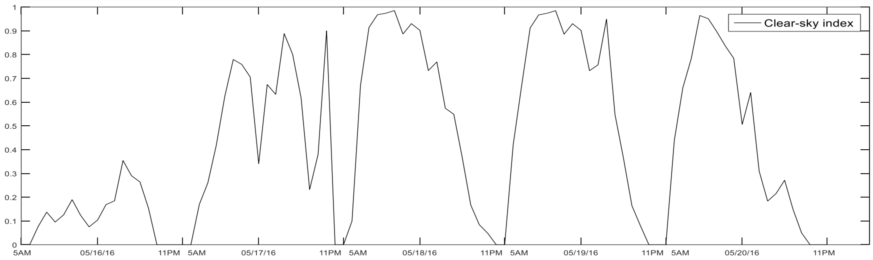

Figure 3. The clear-sky index at the site of Abakan.

The MAFN $Fes_{jhq}(x_h^t)$ is fulfilled based on the data:

$$z_h^t=(x_h^t=(G0_h^t, C_h^{t-2}, P_h^{t-2}, Cl_h^t, T_h^t, Pr_h^t, W_h^t, Wd_h^t), P_h^t), \tag{3}$$

where $G0_h^t$ is the extraterrestrial irradiance, P_h^t is the power from a PV system, P_h^{t-2} is the historical data of the power from a PV system, C_h^{t-2} is the historical data of clear-sky index, Cl_h^t is the cloudiness (%), P_h^t is the pressure, W_h^t and Wd_h^t are the wind speed and the wind direction, respectively, T_h^t is the ambient temperature, $h=\overline{5..23}$, $t=\overline{1..730}$. Notice that Cl_h^t, P_h^t, W_h^t, Wd_h^t, T_h^t are daily average parameters of the weather forecast. The number of samples is 13870 ($h*t=19*730$=13870). This database was collected at the site of Abakan (91.4° of longitude East, 53.7° of latitude North and 246 m of altitude) from March 2016 through February 2018.

3. The training algorithms of the MAFN

The main objective of this research is to fulfill the MAFN for hourly power forecasting for a PV system. The agents of the MAFN are fulfilled as two-layered recurrent networks. The two-layered recurrent networks architecture's parameters (delays, weights and biases) have been coded into particles a. In order to train the effective agents of the MAFN for hourly power forecasting for a PV system the multi-dimensional PSO (Fig. 4) and the Levenberg-Marquardt algorithm have been elaborated. In this research we define a fitness function $f(x)$ based on the Chebyshev criterion as follows:

$$e = f(x) = \max_{i=1..N}\left(\left|P_i(x) - I_i(x)\right| / P_i(x)\right), \tag{4}$$

where N is the number of data samples, $I_i(x)$ is the forecasted power of the PV system, $P_i(x)$ is the cumulative power of the PV system.

The standard Levenberg-Marquardt algorithm [2] can be briefly described as follows:

Step 1. We initialize the weights (in this research the value of a parameter μ is 0.01).

Step 2. We compute the train error $f(w)$ according equation (4).

Step 3. We calculate the increment of weights Δw as follows:

$$\Delta w = [J^T J + \mu I]^{-1} J^T e,$$

where J is the Jacobian matrix, μ is the learning rate which is to be updated using the β depending on the outcome.

Step 4. We update $w = w + \Delta w$. We recomputed the trial train error $f'(w)$ according (4).

Step 5. IF $E'(w) < E(w)$ THEN $w = w + \Delta w$; $\mu = \mu\beta$; Go to step 2: ELSE $\mu = \mu/\beta$; go to step 4 END IF.

MD PSO (termination criteria: $\{IterNo, \varepsilon_C, \ldots\}$) For $\forall a \in \{1, S\}$ do : Randomize $xd_a(0)$: Dimension component of particle a, $vd_a(0)$: Velocity component of dimension of particle a, Initialize $x\tilde{d}_a(0) = xd_a(0)$, $x\tilde{d}_a$: Personal best dimension component of particle a,
For $\forall d \in \{D_{\min}, D_{\max}\}$ do : Randomize $xx_a^d(0)$, $xv_a^d(0)$, Initialize $xy_a^d(0) = xx_a^d(0)$. End For. End For.
For $\forall t \in \{1, IterNo\}$ do : For $\forall a \in \{1, S\}$ do : If $(f(xx_a^{xd_a(t)}(t)) < \min(f(xy_a^{xd_a(t)}(t-1)), \min_{p \in S-\{a\}}(f(xx_p^{xd_a(t)}(t)))))$ then do $xy_a^{xd_a(t)}(t) = xx_a^{xd_a(t)}(t)$
If $f(xx_a^{xd_a(t)}(t)) < f(xy_{gbest(xd_a(t))}^{xd_a(t)}(t-1))$ then $gbest(xd_a(t)) = a$, $gbest(d)$: Global best particle index in dimension d,
If $f(xx_a^{xd_a(t)}(t)) < f(xy_a^{x\tilde{d}_a(t-1)}(t-1))$ then $xd_a(t) = xd_a(t)$, If $f(xx_a^{xd_a(t)}(t)) < f(x\hat{y}_{dbest}(t-1))$ then $dbest = xd_a(t)$ End If. End For.
If the termination criteria are met, then Stop. $xy_{aj}^{xd_a(t)}(t-1)$: jth component of the personal best ($pbest$) position of particle a, in dimension $xd_a(t)$
For $\forall a \in \{1, S\}$ do : For $\forall j \in \{1, xd_a(t)\}$ do :

Compute $ux_{a,j}^{xd_a(t)}(t+1) = w(t)ux_{a,j}^{xd_a(t)} + c_1 r_{1,j}(t)(xy_{a,j}^{xd_a(t)}(t) - xx_{a,j}^{xd_a(t)}(t)) + c_2 r_{2,j}(t)(x\hat{y}_j^{xd_a(t)}(t) - xx_{a,j}^{xd_a(t)}(t))$,

$$xx_{a,j}^{xd_a(t)}(t+1) = \begin{cases} xx_{a,j}^{xd_a(t)}(t+1) + ux_{a,j}^{xd_a(t)}(t+1) & \text{if } X_{\min} \le ux_{a,j}^{xd_a(t)}(t+1) \le X_{\max} \\ U(X_{\min}, X_{\max}) + xx_{a,j}^{xd_a(t)}(t+1) & \text{else} \end{cases},$$

$$xx_{a,j}^{xd_a(t)}(t+1) \leftarrow \begin{cases} xx_{a,j}^{xd_a(t)}(t+1) & \text{if } X_{\min} \le xx_{a,j}^{xd_a(t)}(t+1) \le X_{\max} \\ U(X_{\min}, X_{\max}) & \text{else} \end{cases}. \text{ End For.}$$

Compute $vd_a(t+1) = \lfloor vd_a(t) + c_1 r_1(t)(x\tilde{d}_a - xd_a(t)) + c_2 r_2(t)(dbest - xd_a(t)) \rfloor$,

$$xd_a(t+1) = \begin{cases} xd_a(t) + vd_a(t+1) & \text{if } VD_{\min} \le vd_a(t+1) \le VD_{\max} \\ xd_a(t) + VD_{\min} & \text{if } vd_a(t+1) < VD_{\min} \\ xd_a(t) + VD_{\max} & \text{if } vd_a(t+1) > VD_{\max} \end{cases}, \quad xd_a(t+1) \leftarrow \begin{cases} xd_a(t) & \text{if } P_d(t+1) \ge \max(15, xd_a(t+1)) \\ xd_a(t) & \text{if } xd_a(t+1) < D_{\min} \\ xd_a(t) & \text{if } xd_a(t+1) > D_{\max} \\ xd_a(t+1) & \text{else} \end{cases}. \text{End For. End For}$$

Figure 4. A multi-dimensional PSO.

With the encoding of the MAFN structure into particles, multi-dimensional PSO provides not only the positional optimum in the error space, but as well the optimum dimension of space of a task and the dimensional optimum in the neuronet structure space.

4. Fulfilment of the MAFN

In order to train the effective agents of the MAFN for power forecasting for a PV system the multi-dimensional PSO and the Levenberg-Marquardt algorithm have been combined. The dimension range of the multi-dimensional PSO is $(D_{\min} = 36, D_{\max} = 146)$ (figure 4).The multi-dimensional PSO is first applied to globally optimize the network's structure (the PSO will stop after a global solution is localized within small region), and then the Levenberg-Marquardt algorithm is used to speed up a convergence process. The algorithm of the agent's interaction (figure 5) uses a fuzzy-possibilistic method [3-4]. Fulfilment of the MAFN briefly can be described by figure 6.

for each $agent_q$ in $subculture\ S_k$ do $g_{khq}(x_h^t) \leftarrow$ GetResponse($agent_q$; x_h^t);

$v_q \leftarrow$ TakeAction($g_{khq}(x_h^t)$): Evaluate e_q as (4); $v_q = 1 - e_q$.

end for. $w=[g_{kh1}(x_h^t), \ldots, g_{khq}(x_h^t)]$Calculate $I_h = Fes_{jh}(g_{jhq}(s))$ based on $(w, [v_1, \ldots, v_q])$ as fuzzy expected solution (Fes) in 2 steps [3]

Step 1: Solve equation $\left[\prod_{i=1}^{q}(1+\lambda w_i)-1\right]/\lambda = 1, \quad -1<\lambda<\infty.$

Step 2: Calculate $s = \int h \circ W_\lambda = \sup_{\alpha\in[0,1]} \min\{\alpha, W_\lambda(F_\alpha(v_j))\}$, where $F_\alpha(v_j) = \{F_i | F_i, v_j \geq \alpha\}, v_j \in V$,

$$W_\lambda(F_\alpha(v_j)) = \left[\prod_{F_i\in F_\alpha(v_j)}^{k}(1+\lambda w_i)-1\right]/\lambda.$$ Calculate $\mathrm{I_h} = \max_{v_i \in V} s(w_j)$

Figure 5. Algorithm of the agent's interaction.

I unit: Training of the multi-agent adaptive fuzzy neuronet briefly can be described as follows

All samples ($N=h*t=19*730=13870$) were classified into two groups: A_1 – sunny hour ($T_h^t=1$), A_2 – cloudy ($T_h^t=-1$). This classification generates vector with elements T_h^t. Two-layer recurrent network (number of hidden neurons and delays are 7 and 2, respectively): $F(X)$ was trained. The vector x_h^t was network's input. The vector T_h^t was network's target. Fuzzy sets A_j, (A_1 – sunny hour, A_2 – cloudy) with membership function $\mu_j(s)$ are formed base on aforementioned two-layer recurrent network $F(s_h^t)$, $j=\overline{1..2}$.

We train based on an optimization algorithm o (if $o=1$ then optimization algorithm is multi-dimensional PSO, if $o=2$ then optimization algorithm is Levenberg-Marquardt algorithm, if $o=3$ then optimization algorithm is the proposed algorithm) three two-layered recurrent neural networks: $g_{jhq}(x_h^t)$, $h=\overline{1..19}$, $j=\overline{1..2}$, $q=\overline{1..3}$, based on the data (3). This step provides recurrent neural networks which create the forecasted power of the PV system $g_{jhq}(x_h^t)$. Two agent's subcultures S_j are formed base on aforementioned two-layer recurrent networks.

If-then rules are defined as: Π_j: IF X is A_j THEN $I_h = Fes_{jh}(g_{jhq}(x_h^t))$. (5)

II unit: Simulation of the trained multi-agent adaptive fuzzy neuronet $\forall c \in \{702..730\}$ for $h=1:19$

Aggregation antecedents of the rules (5) maps input data x_h^c into their membership functions and matches data with conditions of rules. These mappings are then activates the k rule, which indicates the k hour's state $k=\overline{1..2}$ and k agent's subcultures – S_k.

According the k hour's state the multiagentny adaptive fuzzy neuronet (trained base on the data s_h^d, where $d=\overline{1..c-1}$) creates the forecasted power of the PV system $I_h = Fes(f_{jhq}(s_h^c))$ as a result of multi-agent interaction (Fig. 5) of subculture S_k.

Figure 6. Fulfilment of the MAFN.

Figure 6 shows the units of the proposed MAFN. The fuzzy-possibilistic method allows for the forecasting of the value of the power from the PV system in a flexible manner, so as to take into account the responses of all agents based on fuzzy measures and the fuzzy integral.

5. Results

To illustrate the benefits of the MAFN in two days ahead forecasting of the hourly power from the PV system, the numerical examples from the previous sections are revisited using the software [4-5]. There the three MAFN were fulfilled based on the training set of the data (3) $t=\overline{1..702}$. The first MAFN1 was trained using multi-dimensional PSO ($o=1$). Due to obtain statistical results, we perform 120 MD PSO runs with following parameters: $S=250$ (we use 250 particles), $E=150$ (we terminate at the end of 150 epochs). Forecast accuracies of the aforementioned models are evaluated as the fitness function (4). Table 1 shows that only one set of MAFN architecture with $dbest=56$ can achieve the fitness function (4) under $4{,}8\ \%$ over the holdout set of the data (3), $t=\overline{702..730}$.

Table 1. Results of multi-dimensional PSO.

The MAFN's dbest dimension	36	46	56	66	76	86	106	116	126	136	146
The fitness function (4) (%)	4.93	4.90	4.78	4.92	4.93	4.95	4.99	5.00	5.02	5.06	5.07

We chose MAFN1 solution with $dbest=56$ as an optimum multi-agent adaptive fuzzy neuronet. The MAFN1 has three agents of each subculture S_k. The aforementioned agents are the two-layered recurrent neural network. The first and second agent's number of hidden neurons and delays are 2. The third agent's number of hidden neurons and delays are 1 and 2, respectively. MAFN2 has same architecture. The second MAFN (MAFN2, $o=2$) was trained by Levenberg-Marquardt algorithm. The third MAFN (MAFN3, $o=3$) was trained by the proposed algorithm, in which the multi-dimensional PSO is combined with the Levenberg-Marquardt algorithm. We applied the multi-dimensional PSO to globally optimize the MAFN's structure based on the training set of the data (3), and then we used the

Levenberg-Marquardt algorithm to speed up a convergence process. Figure 7 shows the mean convergence curves of the multi-dimensional PSO and the proposed algorithm for training a MAFN.

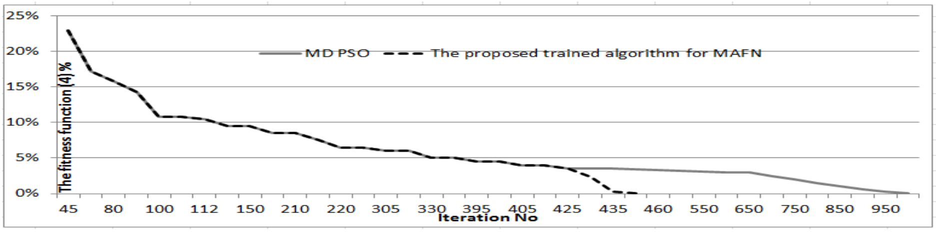

Figure 7. The mean convergence curves.

Figure 7 shows that the MAFN3 has definitely more convergence speed over training set of the data (3), $t=\overline{1..702}$, than the MAFN1 in the power forecasting for the PV system.

Table 2 shows that errors (4) of the three MAFNs in sunny hours are quite small.

Table 2. A two days ahead forecasting of the hourly power from the PV system: comparison of results.

The MAFN with dbest=56	MAFN3 solution		MAFN1 solution		MAFN2 solution	
	Sunny	Cloudy	Sunny	Cloudy	Sunny	Cloudy
The fitness function (4) (%)	3,81	4,71	3,84	4,78	4,71	5,88

The performances of the MAFN1 and the MAFN3 are changing in sunny and cloudy hours (table 2). Nevertheless, the MAFN1 and the MAFN3 effectively track the complex dynamics of real measured data in cloudy hours. Table 2 indicates that the MAFN3 outperform the MAFN2 and the MAFN1, especially in the cloudy hours. The performance of the MAFN3 trained by proposed algorithm in which the multi-dimensional PSO is combined with the Levenberg-Marquardt algorithm is superior to the same one trained by multi-dimensional PSO or Levenberg-Marquardt algorithm, especially during fast fluctuations of cloudiness. Simulation comparison results for a two days ahead forecasting of the hourly power from the PV system demonstrates the effectiveness of the MAFN trained by the proposed algorithm as compared with the same ones trained by multi-dimensional PSO or Levenberg-Marquardt algorithm. The analysis of the evolving errors shows the potential of the MAFN in the hourly power forecasting for a PV system.

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